UNIVERSITY OF TARTU

Faculty of Social Sciences

School of Economics and Business Administration

Lana Botchorishvili

THE EFFECT OF FALSE NEWS ON SYSTEMIC RISK AND SENTIMENT INDICATORS IN THE US

Bachelor Thesis

Supervisor: Lecturer and Research Fellow Mustafa Hakan Eratalay

Tartu 2021

I have written this Research paper/Bachelor Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Table of contents

Introduction

The following paper will be addressing the effect false news might have on systemic risk and sentiment indicators in the US. The topic was chosen for research due to the exponentially ubiquitous nature of obtaining information through internet in the field of economics. This advanced tool paves way for the accumulation of large amounts of information, as online news journals or social media websites, which seem to be the dominating source of news for most Americans (Gottfried & Shearer, 2016), lack adequate third-party filtering due to the rapid information turnover and countless independent users (Allcott & Gentzkow, 2017). As the information pool gets larger and more incessantly changing, it is increasingly difficult to filter out the false news from the real ones. The negative effect of false news is evident, although in some fields (politics) more than others (finance), as their spread is more rapid than that of real news, perhaps due to their provocative nature and pointed tone (Vosoughi et al., 2018).

While systemic risk is not a frequently discussed topic, its influential nature cannot be denied, certainly not after the financial crisis of 2008, which is, primarily, what prompted the concept to be put under scrutiny (C. T. Brownlees & Engle, 2011). The notion refers to the risk of collapse of an entire economic system, similarly to the financial crisis of 2008 or Wall Street Crash of 1929, due to an event occurring within the frame of one of its components, namely, a company (C. T. Brownlees & Engle, 2011); Kaufman & Scott, 2003). One might speculate that, in the event that false news, which, we've established usually aims to elicit a reaction, has high enough impact on systemic risk, manipulating it might cause drastic economic changes.

Unfortunately, no study has been found to examine systemic risk alongside false news, hence no observed relationship is established between the two.

Research question: does false news have any effect on systemic risk and market sentiment indicators?

Research aim: find out if false news has any effect on systemic risk, and sentiment indicators. The research tasks are as follows:

- Define the concepts of systemic risk, sentiment indicators and fake news;
- Find what has been found to affect systemic risk and sentiment indicators;
- Define research method and variables in the data;
- Find the effect of fake news on systemic risk and sentiment indicators and compare findings to the previous studies.

Keywords: statistics, correlation analysis, multivariate analysis, systemic risk, regression

1. Theoretical Basis for False News and Systemic Risk

1.1. Definition of the main concepts

The term “fake news” is nothing new, especially post US presidential election in 2016 (Allcott & Gentzkow, 2017), which is dubbed to be the high time for the “post-truth” phenomenon (Wang, 2016). Due to its popularity during this period, the term seems to have transformed into one that was widely misused as a superficial label, but was redefined by scholars as “objectively verifiable” term of “false” news, or rather: “any story or claim with an assertion in it and a rumour as the social phenomena of a news story or claim spreading […] through the […] network”, which “has been verified to be” “a distortion of the truth” (Vosoughi et al., 2018, p.1). Kogan, Moskowitz and Niessner (2019, p.1) define the term as “a form of disinformation, including hoaxes, frauds, or deceptions, designed to mislead consumers of news.”, while Allcott & Gentzkow (2017, p. 213) refer to it as “news articles that are intentionally and verifiably false, and could mislead readers”. The latter two share the sentiment of the news being false intentionally and purposefully, while the former retains its objectivity and is content with verifying its fictitious nature.

Similarly to the term “fake news”, discussion on the topic of systemic risk became heated after the financial crisis of the 2007-2009 (Borovkova et al., 2017), which prompted a debate over what caused it and how it could have been prevented. The research following the pivotal event concentrated on the components of systemic risk and the ways to predict it. Franklin Allen and Elena Carletti (Allen & Carletti, 2010, p. 3) describe systemic risk as “a situation where many (if not all) financial institutions fail as a result of a common shock or a contagion process.”. The concept entails collapse of the financial system, with emphasis on a component of the market failing to perform, thus, disbalancing the entirety of the framework enough to cause a financial crisis. The measure is difficult to quantify into one variable, since it ought to encompass the entire economic system, including all the different components: companies, banks, the government; measures: asset prices, component size, sentiment; and policies: monetary, fiscal. This leads to a lot of research being dedicated to deriving measures of systemic risk, designed to predict, and warn against the future threats of financial collapse.

Sentiment indicators refer to the consensus on the expected market state, whether market has bullish (confident, optimistic that the prices will go up) or bearish (negative, convinced that the prices will go down) leanings (Palmas, 2020). Private and institutional investors cultivate opinions or sentiment about the state of the economy, which, when aggregated, form market sentiment. Sentiment indicators, such as Shiller Crash confidence index (Barone-Adesi et al., 2012), bullish-bearish spread (*AAII Investor Sentiment Survey | AAII*, n.d.) or business confidence index (*Leading Indicators - Business Confidence Index (BCI) - OECD Data*, n.d.) are used to derive the consensus regarding market health and dictate future actions of the economy. General public often uses them as an indicator for allocating investment opportunities.

1.2. Existing Literature on False News, Systemic risk, and Sentiment indicators

In the modern age the news is often emphasized to be dubious in its validity, and while questioning the reliability of information is conducive to good journalism, the sheer size and spread of news datasets online make it impossible to establish a system for validating the entirety of the data. This is of consequence as the news holds significant importance in our perception of the reality, which is ultimately what dictates our actions. As such, news is bound to drive us to act in all matters, including the economics, making it subjective to changes in what news are delivered, as well as how they are delivered. Borovkova et al. (2017) offer a good example in the form of the UK referendum regrading leaving the EU, which was heavily influenced by the sentiment displayed in the news, effectively altering reality for the voters. Borovkova et al. (2017) focus on exploring the Thomson Reuters News Archive to construct a sentiment-based systemic risk indicator – SenSR – on the basis of “Systematically Important Financial Institutions (SIFIs)”, since these companies hold enough financial power to, in case of a destabilizing event inside of their framework, trigger a collapse of an entire financial system of a state (Borovkova et al., 2017, p. 3). SenSR is found to be a strong predictor of systemic distress up to 12 weeks before it takes place, proving that news sentiment has strong enough impact on systemic risk to be used as a predictive measure (Borovkova et al., 2017).

The effect of news is not limited to short term decisions of the public, it also spreads to long term measures of market health. Heston & Sinha (2016) find that news sentiment has an effect on stock market returns, with weekly aggregated news having more prolonged effect, lasting up to a quarter, as opposed to daily news, which last only a couple of days. It can be speculated that the news has more of an impact over longer period of time, since the investors require more than one day in order to process the news and generate a response, or their response takes some time to affirm they have had significant effect on the market. The effect of negative news lasts considerably longer than that of the positive news (Heston & Sinha, 2016), perhaps due to the combined impact of people’s inclination to dwell on negative feedback and the pointed tone of the negative news.

News stories have also been found to have "a systematic link […with…] the magnitude of the momentum and long-term reversal effect in its stock" (Hillert et al., 2014, p. 33), further corroborating that news sentiment is able to alter the investor behaviour and be an underlying cause of market momentum. Although the reaction to the news may not always be rational, as over-reaction has been found to precede a large change in the market (Hillert et al., 2014). This has also been found to be the case with systemic risk: on the example of the financial crisis of 2008, leading up to large amounts of financial distress, the market sentiment shows signs of overconfidence and excessive optimism, as well as lack of anxiety (Nyman et al., n.d.), causing the investor behaviours to be being labelled as a "madness" in the beginning of 2007 (Barone-Adesi et al., 2012).

The period of 2007-2009 is also characterized by unusually high P/E ratio adjusted for inflation. Historical highs of the indicator reaching and staying 25 are known to be rare and have only been observed during the times of financial distress (Barone-Adesi et al., 2012).

While the overall news sentiment has been proven as an underlying cause of investor activity and possible predictor of systemic risk, fake news has only been explored in the context of general effect on the market, its impact on exacerbating financial distress, to end up causing a full-scale crisis still unknown. Kogan et al. (2019) have brought out the impact of false news on financial markets by taking 3 datasets: a small, but comprehensive sample of 171 articles, a larger and more general sample of more than 350 thousand articles dating 2005-2015 and a qualitative dataset showing the response of the market to the release of false news. The results show higher degree of responsiveness to the fake articles, as opposed to the real ones, which seems to be a reoccurring trend through both theory and quantitative analysis (Kogan et al., 2019). The days following release of a fake news article have 50% more increase in the abnormal trading activity than the release of legitimate news. Notably, "larger influence of fake articles likely stems from [them], by design, being crafted to attract more attention and influence." (Kogan et al., 2019, p. 6). However, despite the initially strong response, the trading activity is found to remain unresponsive to news of any kind on a platform: legitimate or fake, after the public is made aware of the false nature of the released news content.

Clare et al. (2019) find that despite generating more attention than legitimate news, possibly due to the reasons explained by Kogan et al.(2019), stock market reaction is appropriately faint, when compared to the reaction caused by the legitimate news. The conflict between the two studies could be attributed to the latter having a bigger sample size of 383 fake news articles, as opposed to 171 in Kogan et al. (2019), as well as access to real investor reactions. Both studies use the Securities and Exchange Commission (SEC) crackdown of stock promotion schemes in 2017, which exposed several hundred fake news articles for having been written on commission, with personal agenda in mind (Clarke et al., 2019).

Barone-Adesi et al (2012) address the relationship between the asset prices, market sentiment and systemic risk. While the time between 2004 and 2007 is characterized by optimistic investor sentiment an overconfidence, as evidenced by the raise in several sentiment indices and optimism, the crash confidence index declined sharply after reaching its peak in the February of 2007, indicating that more and more investors started to realize that the market crash was imminent. Shortly after the bankruptcy of Lehman Brothers, which one of the major events leading to financial panic in 2008, optimism reached its new low, followed by systemic risk raising to 25% only wo months later. It is conjectured that sentiment played a big role in driving systemic risk upward by “fostering the climate in which systemic risk grew” (Barone-Adesi et al., 2012, p. 3).

Some papers have explored the cases of misinformation causing changes in investment allocation, one such example being the US stock market losing more than 130 billion USD due to a false tweet from the Associated Press, which was later discovered to have been hacked into (Rapoza, 2017). The study of Vosoughi et al. (2018), along with the aforementioned example, investigates the spread of false news based on the data of approximately 126 thousand stories obtained from Twitter from 2006 to 2017. Validity of the news is examined using six different methods, labelling a story false or true with a certainty of almost 98%.

Table 1
Overview of literature

Author	Year	Source	Data	Focus
Nyman et al.	n.d. (presumed 2018)	Thomson Reuters News Archive	2000 – 2013 Monthly data	Emotional narrative driving economic changes
Borovkova S., Garmaev E., Lammers P. & Rustige J	2017	Thomson Reuters News Archive	2003 – 2016 Weekly data	Constructing a systemic risk indicator based on media sentiment
Kogan et al.	2019	Seeking Alpha; Motley Fool	2005-2015	Impact of false news on financial markets
Vosoughi et al.	2018	Twitter	2006-2017	Spread of false news
Heston & Sinha	2016	Thomson Reuters News Archive/ NewScope	2003-2010	Impact of news on the sentiment of stock market investors

Source: Compiled by the author

2. Empirical research on false news, sentiment, and Systemic risk

2.1. Methodology and data

The majority of previous literature base their news sentiment studies on the data obtained Thomson Reuters news archive studies (Borovkova et al., 2017; Heston & Sinha, 2016; Nyman et al., n.d.). Heston & Sinha (2016) conduct their research using more than 900 thousand news stories from the Thomson Reuters News archive, containing the publication date, story ID, news text, over the years 2003 to 2010 to extrapolate their impact on stock returns. In order to measure the sentiment of the news they use the Thomson Reuters NewScope data, which contains the time of the publication, staleness of the article, several indicators identifying and rating the relevance of the company mentioned in the article, as well as the measures of sentiment. The two datasets are joined through story IDs and times of publication. Later, summary statistics and cross-sectional regression analysis is conducted in order to find the predictive quality of the news sentiment. The news sentiment is aggregated to weekly basis, which increases the window of impact. (Heston & Sinha, 2016)

Borovkova et al. (2017) choose to construct their systemic risk indicator from the Thomson Reuters news archive and Thomson Reuters Analytics Engine (TRNA) data spanning the period of 2003 to the beginning of 2016, including – along with the essentials, such as article date, headline, source, etc. – relevance score of the piece of news for a particular company, news sentiment score: a normalized indicator showing positive, negative, and neutral sentiment of the news, and novelty score. The sentiment is aggregated weekly, similar to Heston & Sinha (2016).

Nyman et al. (n.d.) in their Bank of England working paper use three sets of big data: Bank of England internal market commentary, which consists of 26 reports on financial markets and system per month, during the span of 10 years, from 2000 to 2010; Broker reports, which is made up of 100 documents per month from 2010 to 2013, provides macroeconomic information regarding financial markets; lastly, Reuters News Archive provides 17 million English news articles on macroeconomic trends and makes up for the sentiment portion of the analysis. The former two of the data sources illustrate the state of financial markets during the span of 2000 – 2013, while the latter dataset attempts to complement them with the news articles released during that period and, thus, justify some of the major economic trends. Monthly sentiment of the text is calculated by subtracting the number of anxiety words from the number of excitement words and weighting the result with the size of the text. (Nyman et al., n.d.)

Heston & Sinha (2016, p. 2) measure systemic risk with Marginal Expected Shortfall (MES) “defined for a firm as the expected equity loss per dollar conditional on the occurrence of a systemic event”. Sentiment of the market is measured by several sentiment indicators, such as: crash confidence index by Robert Shiller, Baker-Wurgler sentiment index and Campbell-Shiller P/E. The study, after deriving their own measure of sentiment, proceeds to conduct time series analysis of the data.

2.2. Overview of data

Since the previous studies base their papers on Thomson Reuters News Archive (Borovkova et al., 2017; Heston & Sinha, 2016; Nyman et al., n.d.) or Securities and Exchange Commission (SEC) fake news articles (Clarke et al., 2019; Kogan et al., 2019), the following empirical research should be conducted using one of these datasets. However, due to the hardships of obtaining data from both, and the easy access to a dataset on the website of the University of Victoria, a Canadian research university, it was deemed appropriate to use the one readily available (*About the University - University of Victoria*, n.d.). The dataset consists of fake and real news articles (only the fake news will be used in this research), along with the date of publishing, title, article text, and subject (*Fake News Detection Datasets - University of Victoria*, n.d.).

Since the news dataset does not include the sentiment scores like the Thomson Reuters NewScope data (Heston & Sinha, 2016) or TRNA (Borovkova et al., 2017), we need to derive the sentiment of the fake news articles by quantifying sentiment of the text. There are several open-source lexicon-based analysers that are used for determining sentiment of a text by labelling the words within as positive, negative, or neutral. VADER (Valence Aware Dictionary and sEntiment Reasoner) is one such Python-compatible analysis tool (Hutto & Gilbert, 2014). The instructions for its usage are openly accessible and well-documented. Unlike other similar libraries, the tool takes into account punctuation, capitalization, slang words, emojis, and sentiment strength of the words (e.g. “okay” would be less positive than “marvellous”). The VADER analyser assigns three polarity values to each word: positive, negative and neutral. A weighted compound score is then calculated as a measure of general sentiment. The compound score is normalized to lie between -1.0 to 1.0, from extremely negative to extremely positive. The threshold values are as follows:

- Positive sentiment: compound score >= 0.5
- Neutral sentiment: -0.5 < compound score < 0.5

- Negative sentiment: compound score <= -0.5

SRISK is one of the most well-known systemic risk indicators derived for measuring expected capital shortfall, given market decline of 10%. The indicator can be interpreted as the total amount of capital the government is expected to supply the financial system with, in order to halt a market crisis (C. Brownlees & Engle, 2016). SRISK is able to provide predictive measure for financial distress leading up to a crisis. Systemic risk index for this study is obtained from the V-Lab database (*V-Lab: Systemic Risk Analysis Summary*, n.d.).

For the sentiment indicators, we have chosen to include Crash Confidence Index (CCI) which is a survey-based indicator, measuring the percentage of respondents who think that the probability of market crash being imminent in the following 6 months is under 10%. The survey question is as follows (*United States Stock Market Confidence Indices | Yale School of Management*, n.d.):

"What do you think is the probability of a catastrophic stock market crash in the U. S., like that of October 28, 1929 or October 19, 1987, in the next six months, including the case that a crash occurred in the other countries and spreads to the U. S.? (An answer of 0% means that it cannot happen, an answer of 100% means it is sure to happen.) [Fill in one number]"

The respondents are divided into individual and institutional investors, although we will only be using the data for the latter, since it has been found to be more informative (Heston & Sinha, 2016). High values of CCI suggest that the investors are highly optimistic that market crash is not probable.

Second sentiment indicator we will be using is AAII investor sentiment survey. The investors are asked the same question each week, regarding their opinion on direction of the stock market, which is then used to calculate the percentages of bullish, neutral, and bearish investors (*AAII Investor Sentiment Survey | AAII*, n.d.). We will be using the bullish-bearish spread (BBS), which is an aggregate sentiment of financial advisors. Negative BBS indicates that more investors are bearish than bullish, while positive BBS indicates the opposite.

Business Confidence Index (BCI) has been chosen to represent the sentiment of the companies. Similarly to the other two indicators, BCI is a survey-based index and reflects the opinions regarding future developments "in production, orders and stocks of finished goods in the industry sector. It can be used to monitor output growth and to anticipate turning points in economic activity." (*Leading Indicators - Business Confidence Index (BCI) - OECD Data*, n.d.). Optimistic outlook on the future business development is reflected with the numbers of over 100, while the numbers below 100 indicate pessimistic outlook on future business performance (*Leading Indicators - Business Confidence Index (BCI) - OECD Data*, n.d.).

The obtained data is as follows:

- Fake news sentiment (FNS) – obtained by calculating polarity scores of 23467 fake news articles from University of Victoria database (*Fake News Detection Datasets - University of Victoria*, n.d.) and aggregated on monthly basis. The data encompasses the period between the 31/3/2015 and 19/2/2018. The sentiment stays in the range of -1 to 1, indicating negative and positive sentiment, respectively.
- Number of articles – obtained by aggregating the number of fake news articles on a monthly basis. The values indicate how many fake articles are released each month. Data encompasses the same time range as FNS.
- SRISK – (SRI) monthly data obtained from V-Lab database (*V-Lab: Systemic Risk Analysis Summary*, n.d.). The unit is in billion US dollars. Represents the amount of capital needed to bail the financial system out of market crash. High SRISK indicates high financial risk. The data encompasses the same time range as FNS.
- Crash Confidence Index (CFI) – monthly data obtained from Yale School of Management website (*United States Stock Market Confidence Indices | Yale School of Management*, n.d.). Represents the percentage of institutional investors who think there is little probability of market crash being imminent in the following 6 months. Measured in percentage. The data encompasses the same time range as FNS.
- Bull-Bear Spread (BBS) – weekly data obtained from AAII Investor Sentiment Survey(*AAII Investor Sentiment Survey | AAII*, n.d.). Positive spread indicates optimistic sentiment regarding the upcoming market movement, negative spread indicated pessimistic sentiment. Measured as the difference in percentage. Aggregated to monthly basis. The data encompasses the same time range as FNS.
- Business Confidence Index (BCI) – monthly data obtained from OECD database (*Leading Indicators - Business Confidence Index (BCI) - OECD Data*, n.d.). Numbers over 100 indicates optimistic outlook on the financial performance, while numbers below 100 indicate pessimistic outlook.

The data will be analysed in three steps:

1. Simple descriptive statistics – to observe overall trends;
2. Correlation analysis – to observe relations between the variables;

3. Multivariate multiple linear regression – to establish the impact our predictors (fake news sentiment and number of fake news articles) have on independent variables (systemic risk and sentiment indicators).

Most of the data manipulation was conducted using RStudio, while most of the statistical analysis was conducted using STATA.

2.3. Research results

The data table (see Appendix A) represents the cross-sectional data gathered for this project. The table includes all the variables discussed above, as well as the number of fake news articles published in the respective month. The sample size for each variable is 35, which is rather small and could increase the risk of inaccuracy in the subsequent tests.

2.3.1. Descriptive analysis

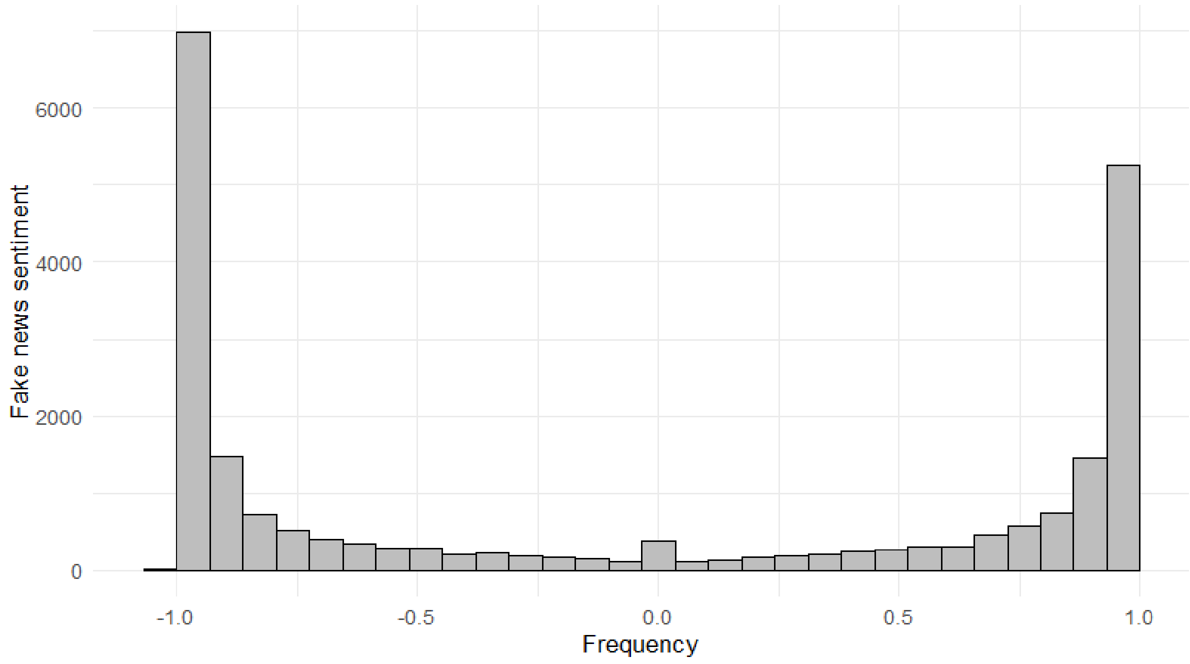


Figure 1. Distribution of FNS

Source: Compiled with RStudio

Before aggregating FNS into monthly data, we will first inspect its compound polarity distribution. As observed on figure 1, sentiment is mostly concentrated at the extremities, with about 40% of articles scoring below -0.8 and 32% of articles scoring above 0.8. The neutral sentiment does not seem to be prevalent among the fake news articles, which is not surprising, since, as previously observed, false news is designed to have a more compelling and authoritative tone in order to attract more attention and response (Kogan et al., 2019). Excessive negative or positive sentiment is conductive to this aim.

The distribution of the sentiment of the fake news articles over time can be observed in figure 2. Each news article is marked according to the subject of the text. We can see that the text sentiment is clearly concentrated on the extremities of the polarity compound score, which is also evident from figure 1, as well as the neutral score of 0. While the left-news dominates the year 2015, the beginning of 2016 sees a surge in the news regarding middle-east, perhaps due to the political debates around the subject becoming more prevalent due to the elections. The articles labelled “News” also come to appear in the year 2016, although it is uncertain what exactly prompted the articles to start being recorded in this category. Majority of the articles are of the category “News”, closely followed by “politics” and “left-news”.

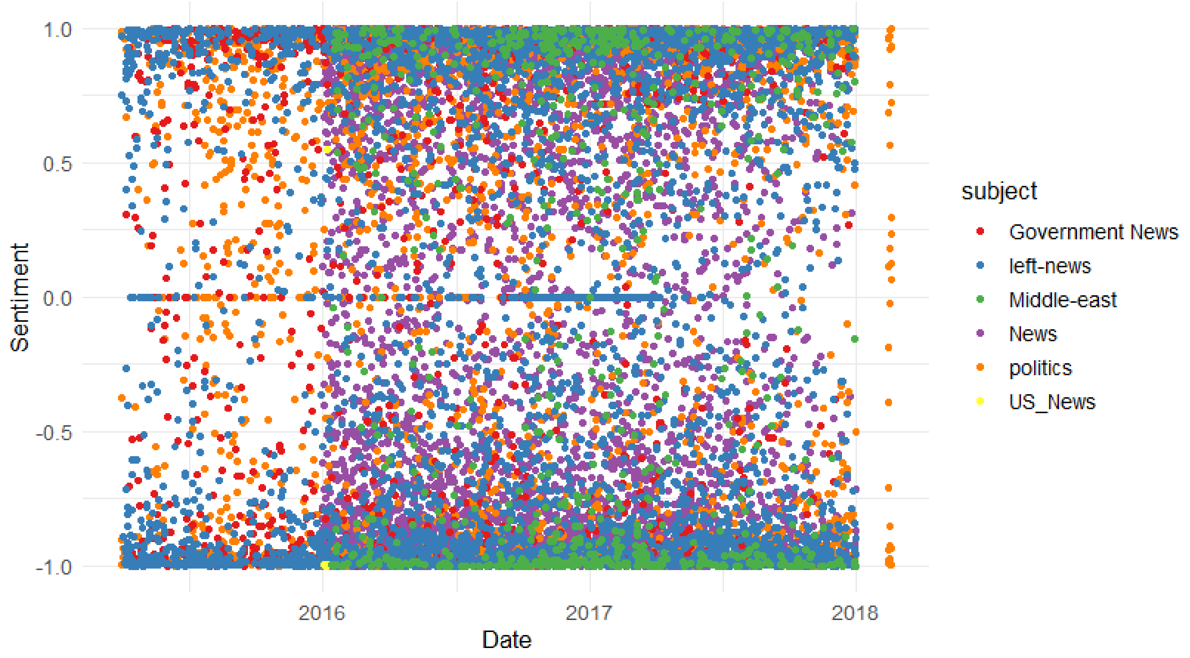


Figure 2. Distribution of text sentiment over time

Source: Compiled using RStudio

Table 2 presents simple descriptive data for all the variables. The measures include number of observations, mean, minimum and maximum values and standard deviation. Despite the large range of news sentiment in the daily data, table 2 shows that the monthly aggregated data appears rather monotone. Minimum and maximum values have changed to -0.223 and 0.271 respectively from -1 and 1. This was to be expected, as aggregating data through means smooths out the noise and gets rid of extremities. While not ideal, aggregating data by months is necessary to normalize the data range across all the variables. Mean value of the variable is negative, indicating that the overall sentiment of fake news has negative leanings, which could also be observed in the daily data.

Number of fake news articles seems to reach its highest value of 1085 around the same time as SRI reaches 506 (see Appendix A), in the beginning of 2016, although they slowly decline after the peak. This trend can be observed in figure 3. While Crash confidence index remains in the midrange for the beginning of 2016, its peak is registered to have occurred in the end of 2015, a couple of months before SRI and number of fake news articles peaked. The indicator dips to its lowest value at the end of 2016. This movement can be explained by the previous studies finding overconfidence to be present in the market leading up to the financial distress reaching its highest level (Barone-Adesi et al., 2012; Nyman et al., n.d.).

Table 2
Descriptive statistics

Variable	N	Mean	Min	Max	Std. Dev.
FNS	35	-.0605	-.223	.271	-.08899
N	35	652.486	8	1085	329.445
SRI	35	286.26	104	506	103.44
CCI	35	34	25.41	40	3.31
BBS	35	2.097	-20.28	19.1	8.74
BCI	35	100.1	98.85	101.5	.82

Source: Compiled with Rstudio

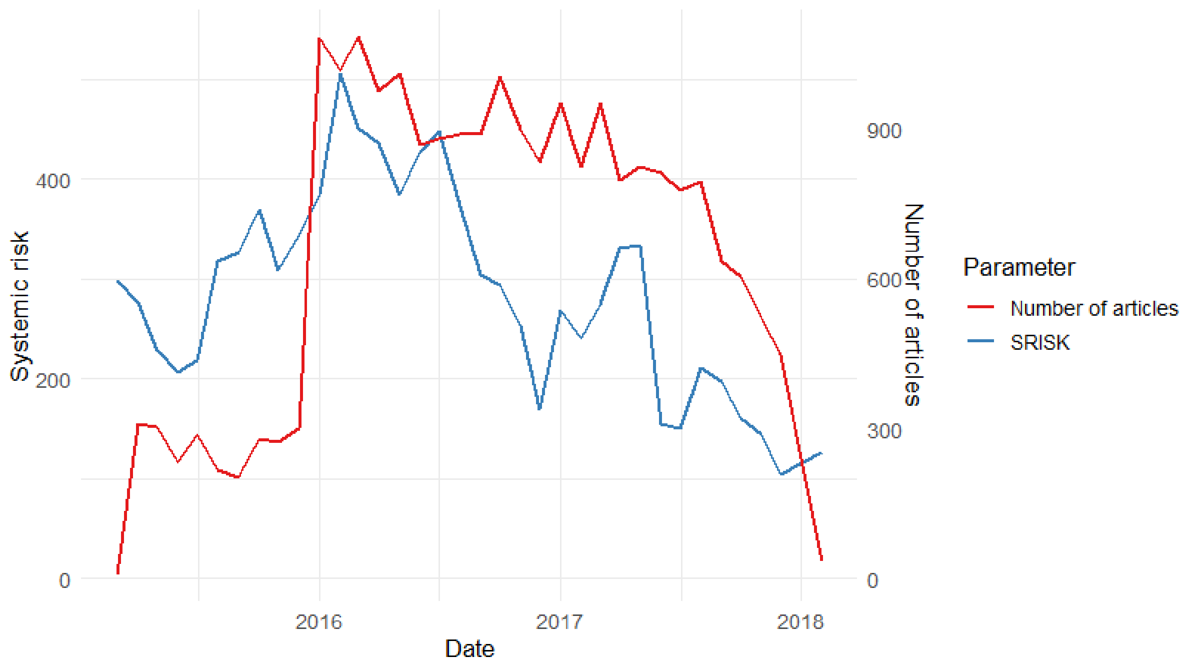


Figure 3. Systemic risk and the number of articles over time

Source: Compiled with RStudio

Highest standard deviation of almost 330 can be observed in the number of articles, perhaps due to the high variation in the data, which is also evident from the difference in its minimum and maximum values. However, this disparity is mostly present in the beginning of 2015, with random variations throughout 2016-2018, all-while the sentiment remains negative. Bull-Bear spread, and Business confidence index retain raising trend all throughout the chosen time period. Their average values suggest that overall outlook on the financial performance is positive, as the mean of BBS is above 0 and BCI is slightly over 100 (see table 2).

2.3.2. Correlation analysis

We chose to use simple Pearson correlation for analysing the relations between the variables, since most of them are scale. The chosen confidence interval is 95%, since it is the default interval in most studies and there is no pressing need to change it, hence the alpha (α) = 0.05. Hypothesises are as follows:

H_0: Correlation is not statistically significant.

H_1: Correlation is statistically significant.

p-value > 0.05 (α) - > Accept H_0.

p-value < 0.05 (α) - > Reject H_0, accept $H_{1.}$

The value of the Pearson correlation indicates the orientation (negativity, positivity) and the strength of the correlation (correlation coefficient (r) < 0.3 => weak correlation; r > 0.7 => strong correlation).

Table 3

Pearson correlation scores and statistical significance

Variable	1	2	3	4	5
1. FNS					
2. N	-.26				
3. SRI	-.07	.38*			
4. CCI	-.02	-.24	.09		
5. BBS	.13	-.34*	-.49**	-.08	
6. BCI	-.08	.02	-.75**	-.05	.43**

Note. * indicates $p < .05$. ** indicates $p < .01$.
Source: Compiled using RStudio

Table 3 shows the correlations between all the computed variables. The coefficients with an asterisk signify that the p-value is less than 0.05, while those with double asterisk signify that the p-value is less than 0.01, indicating that, respectively, we can be 95% or 99% certain that the correlation is statistically significant. From Table 3 we can infer that there is no statistically significant correlation between FNS and any of the other dependent variables. In fact, the correlation coefficient is rather low for all of them, leading us to believe that systemic risk and sentiment indicators are not, in fact, impacted by FNS. We do, however, find that the number of fake news articles has a statistically significant, albeit weak (0.38), positive relationship with SRI and weak negative relationship with BBS (-0.34).

Since the release of fake news is known to cause temporary reaction in the market trading activity (Kogan et al., 2019), perhaps this could be the underlying cause of the weak positive relationship between N and SRI, as well as the weak negative correlation between N and BBS. The causation could also be reversed: it is possible that the higher number of fake news articles are simply a reaction to large amounts of financial distress and negative sentiment in 2016, which was the year that saw Donald Trump be elected for the president of the United States (Allcott & Gentzkow, 2017).

Statistically significant correlation can also be observed between the dependent variables. Systemic risk has strong negative statistically significant correlation with BCI and average negative correlation with BBS, which is to be expected, as sentiment about the future market performance is known to play a key role in driving systemic risk (Barone-Adesi et al., 2012). The correlation between BBS and BCI is also statistically significant, which is to be expected as they are both indicators of market sentiment. What is surprising, however is the lack of correlation between crash confidence index and any other variable.

2.3.3. Normality test

In order to conduct regression analysis, we need to test the assumptions of the data. Normality test is conducted using Shapiro-Wilk test, due to the observations being less than 50 The confidence interval is set to 95%. The hypothesis for the normality is as follows:

H_0: The data is normally distributed.

H_1: The data is not normally distributed.

p-value > 0.05 (α) => Accept H_0

p-value < 0.05 (α) => Reject H_0, accept H_1

We can see from the normality test (see table 4) that the p-value for all dependent variables is more than 0.05, indicating that we can accept null hypothesis and assume the data is normally distributed. While the independent variables are not normally distributed, since their p-values are less than 0.05, the regression analysis only requires the normality of outcome variables. This means we may proceed with the regression analysis.

Table 4

Shapiro-Wilk normality tests

Variable	Obs	W	V	z	Prob>z
FNS	35	0.91144	3.161	2.402	0.00814
N	35	0.89092	3.893	2.837	0.00227
SRI	35	0.97853	0.766	-0.556	0.71076
CCI	35	0.94224	2.062	1.510	0.06550
BCI	35	0.92444	2.697	2.071	0.01918
BBS	35	0.97990	0.717	-0.693	0.75592

Source: compiled using STATA

2.3.4. Regression analysis

Chosen model for analysis is multivariate multiple linear regression, since we have 2 predictor and 4 dependent variables. The model is as follows:

$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$

$Y_2 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$

$Y_3 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$

$Y_4 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + u$

Dependent variables:

Y_1 – SRISK

Y_2 – Crash confidence index

Y_3 – Business confidence index

Y_4 – Bull-Bear spread

Independent variables:

X_1 – Fake news sentiment

X_2 – N of fake news articles

β_0 – constant regression parameter

β_i – regression parameter for input variable

u – error

n – sample size=35

The hypothesis for the regression model is as follows:

H_0: the model is statistically insignificant.

H_1: the model is statistically significant.

p-value > 0.05 (α) => Accept H_0

p-value < 0.05 (α) => Reject H_0, accept H_1

Due to the presence of more than one predictor variable in the dataset, we use MANOVA test to determine the statistical significance of the regression model. In the MANOVA (Appendix C) table we found that all four measures of multivariate analysis of variance - Wilks' lambda, Lawley-Hotelling trace, Pillai's trace and Roy's largest root – indicate that the model is statistically significant. While there is some variation in the p-values, all of them remain below the α value, leading us to reject H_0 and accept H_1. From the R squared of table 5 we can see that the model explains 17% of the variation in SRI and approximately 12% of variation in BBS, but only 6% in CCI and less than 1% in BCI. The p-values of the dependent variables present statistical significance of the model for SRI.

MANOVA table also shows that the p-values of the predictor variables are divided: p-values of the FNS appear to be above 0.05 in all four tests, indicating that the predictor variable is not statistically significant. On the other hand, the variable N shows the exact opposite – with the p-value of 0.003, the predictor is statistically significant to the model with the certainty of 99% confidence interval.

Table 5

R-squared, F and p-values of the regression model

Equation	Obs	Parms	RMSE	"R-sq"	F	P
SRI	35	3	96.91789	0.1737	3.364297	0.0472
CCI	35	3	3.306378	0.0590	1.003309	0.3779
BCI	35	3	.8436263	0.0071	.1149116	0.8918
BBS	35	3	8.453348	0.1191	2.163209	0.1315

Source: Compiled using STATA

In order to determine whether the independent variables are statistically significant for predicting the individual dependent variables we conduct another hypothesis testing for the coefficients of the predictors:

H_0: $\beta_i = 0$, the predictor is statistically insignificant.

H_1: $\beta_i \neq 0$, the predictor is statistically significant.

Sig. (p-value) > 0.05 (α) => Accept H_0

Sig. (p-value) < 0.05 (α) => Reject H_0, accept H_1

The coefficients table in Appendix C shows that all p-values for FNS are more than the alpha, meaning the independent variable is statistically insignificant for all dependent variables. N demonstrates lower levels of p-values for SRI and BBS, staying at 0.016 and 0.064 respectively. While p-value for BBS is over 0.05, and, hence, statistically insignificant, p-value for SRI is well below the established alpha, which leads us to reject H_0 and accept H_1. We can also assume that the orientation of the effect N has on SRI is positive, since both lower and upper bounds of confidence interval are above 0 (see Appendix C).

The model is only significant for one predictor variable – number of published fake news articles (p = 0.0003) (see Appendix C MANOVA table) and one dependent variable – SRI (p = 0.0472) (see table 5). The variable has statistically significant effect on SRI (p = 0.016) (see table 6) since it's p-value is less than 0.05, indicating that we Reject H_0, and accept H_1. The interpretation of the parameters are as follows:

- Intercept: when all the other variables, in this case, N, are equal to 0, then the number SRISK is 212.2189 billion US dollars.
- Number of fake news articles published: in an economy where the number of fake news published is 1 point (article) higher the SRISK, or the capital required to bail the financial system out of market crash is 0.1335259 units, or 133.5259 million US dollars higher.

Table 6

Regression model for SRI

	Intercept	N
Coeff.	212.2189	.1335259
Std. error	36.87041	.0523047
t	5.76	2.55
p	0.000	0.016

Source(s): Compiled by the author

R^2=0.1737; F=3.364; p=0.0472; n=35

Conclusion

This paper analysed the effect of fake news and its sentiment on systemic risk and sentiment indicators in the USA. The time period considered was 31/3/2015 to 19/2/2018. The paper made use of an open-source python libraries to quantify the fake news sentiment by applying a lexicon-based analysis tool - VADER - to the article text. After aggregating fake news sentiment, number of articles, systemic risk and sentiment indicators to a uniform monthly data we conducted descriptive, correlation and regression analysis to better understand the interconnections between the variables.

We found that the negativity or positivity of fake news does not affect or relate to systemic risk or market sentiment in the US. After aggregating the number of fake news and crossing it over with systemic risk indicator, we found that there is statistically significant relationship between the two. A negative relationship also emerged between the volume of published fake news and the investor sentiment. After estimating a regression model to find the extent of this correlation we found that the volume of fake news articles has considerable impact on the systemic risk, leading us to believe that the volume of published material does indeed affect the amount of financial distress in the market.

List of references

1. *AAII Investor Sentiment Survey | AAII*. (n.d.). Retrieved May 12, 2021, from https://www.aaii.com/sentimentsurvey
2. *About the university - University of Victoria*. (n.d.). Retrieved May 10, 2021, from https://www.uvic.ca/about-uvic/about-the-university/index.php
3. Allcott, H., & Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, *31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211
4. Allen, F., & Carletti, E. (2010). *Financial Connections and Systemic Risk*. http://www.nber.org/papers/w16177
5. Barone-Adesi, G., Mancini, L., & Shefrin, H. (2012). *Sentiment, Asset Prices, and Systemic Risk Chapter Contribution to the Handbook of Systemic Risk*.
6. Borovkova, S., Garmaev, E., Lammers, P., & Rustige, J. (2017). *SenSR: A sentiment-based systemic risk indicator*.
7. Brownlees, C., & Engle, R. (2016). *SRISK: A Conditional Capital Shortfall Measure of Systemic Risk*. http://vlab.stern.nyu.edu/
8. Brownlees, C. T., & Engle, R. (2011). *VOLATILITY, CORRELATION AND TAILS FOR SYSTEMIC RISK MEASUREMENT*.
9. Clarke, J., Chen, H., Du, D., & Hu, Y. J. (2019). *Fake News, Investor Attention, and Market Reaction*.
10. *Fake News Detection Datasets - University of Victoria*. (n.d.). Retrieved May 10, 2021, from https://www.uvic.ca/engineering/ece/isot/datasets/fake-news/index.php
11. Gottfried, J., & Shearer, E. (2016). *News Use Across Social Media Platforms 2016 | Pew Research Center*.
12. Heston, S. L., & Sinha, N. R. (2016). *News versus Sentiment: Predicting Stock Returns from News Stories*. https://doi.org/10.17016/FEDS.2016.048
13. Hillert, A., Jacobs, H., & Müller, S. (2014). *Media Makes Momentum*. https://ssrn.com/abstract=2023442
14. Kaufman, G. G., & Scott, K. E. (2003). What Is Systemic Risk, and Do Bank Regulators Retard or Contribute to It? on JSTOR. *The Independent Review*, *7*(3), 371–391.
15. Kogan, S., Moskowitz, T. J., Niessner, M., Cookson, T., Garcia, D., Gentzkow, M., Gorton, G., Kelly, B., Kempf, E., Moskowitz, B., Pennebacker, J., Shapiro, J.,

Shue, K., So, E., Sosyura, D., & Hartzmark, S. (2019). *Fake News: Evidence from Financial Markets*. https://ssrn.com/abstract=3237763Electroniccopyavailableat:https://ssrn.com/abstract=3237763

16. *Leading indicators - Business confidence index (BCI) - OECD Data*. (n.d.). Retrieved May 12, 2021, from https://data.oecd.org/leadind/business-confidence-index-bci.htm
17. Nyman, R., Gregory, D., Kapadia, S., Ormerod, P., Tuckett, D., & Smith, R. (n.d.). *News and narratives in financial systems: Exploiting big data for systemic risk assessment 1*.
18. Palmas, C. de. (2020). *What Are Market Sentiment Indicators And How To Use It In Your Trading? | The Smart Investor*. https://infoforinvestors.com/investing/technical-analysis/market-sentiment-indicators/
19. Rapoza, K. (2017). *Can "Fake News" Impact The Stock Market?* https://www.forbes.com/sites/kenrapoza/2017/02/26/can-fake-news-impact-the-stock-market/#5e59cbe2fac0
20. *United States Stock Market Confidence Indices | Yale School of Management*. (n.d.). Retrieved May 11, 2021, from https://som.yale.edu/faculty-research-centers/centers-initiatives/international-center-for-finance/data/stock-market-confidence-indices/united-states-stock-market-confidence-indices
21. *V-Lab: Systemic Risk Analysis Summary*. (n.d.). Retrieved May 12, 2021, from https://vlab.stern.nyu.edu/welcome/srisk
22. Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146–1151. https://doi.org/10.1126/science.aap9559
23. Wang, A. B. (2016). *'Post-truth' named 2016 word of the year by Oxford Dictionaries - The Washington Post*. https://www.washingtonpost.com/news/the-fix/wp/2016/11/16/post-truth-named-2016-word-of-the-year-by-oxford-dictionaries/

APPENDIX A

The data

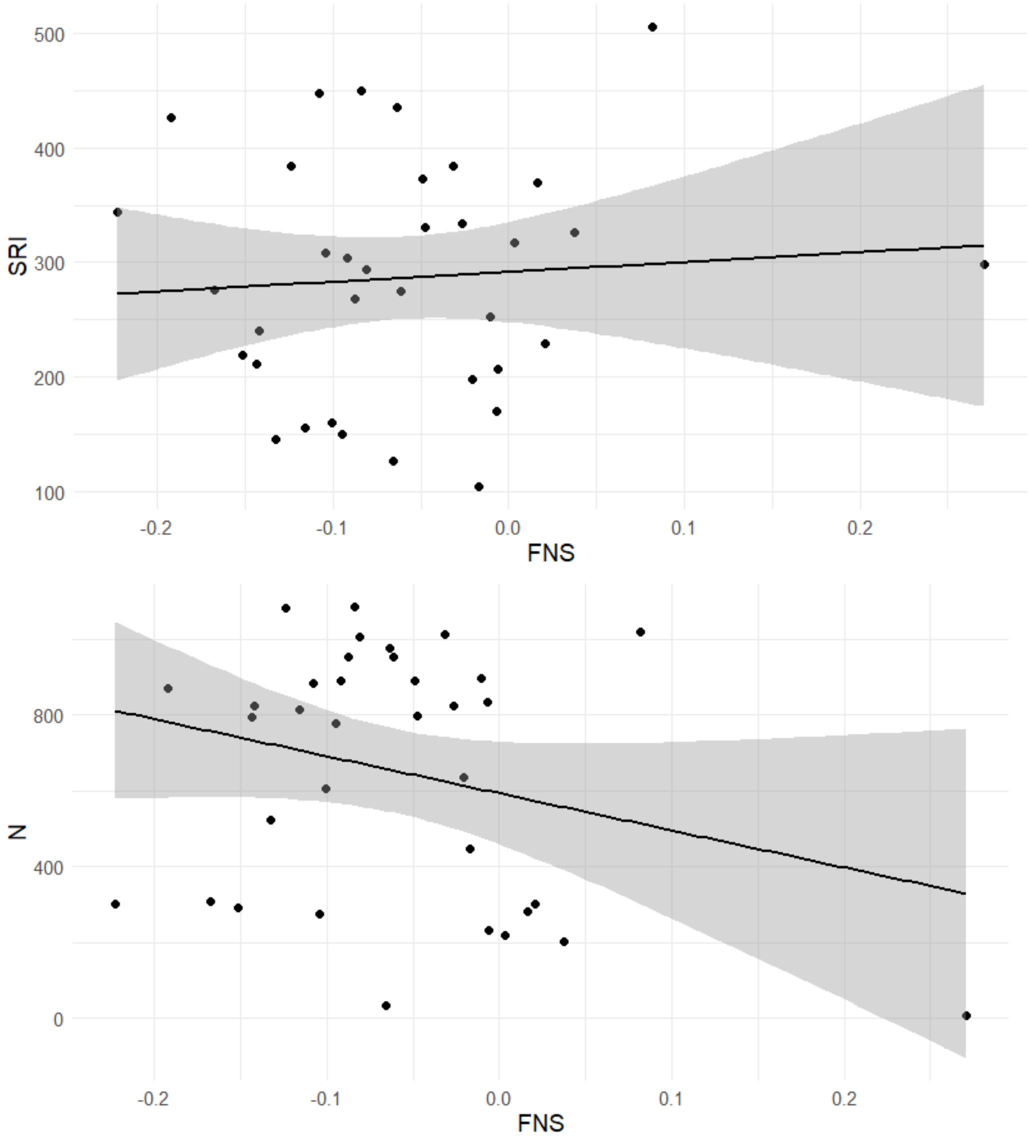
Date	FNS	N	SRI	CCI	BBS	BCI
2015-03-01	0.271	8	298	35.2	8.09	99.84
2015-04-01	-0.167	309	276	34.67	6.89	99.8
2015-05-01	0.021	302	229	34.04	0.67	99.86
2015-06-01	-0.006	232	207	36.2	-1.21	99.85
2015-07-01	-0.151	290	219	34.3	-3.77	99.71
2015-08-01	0.004	219	317	35.52	-6.33	99.5
2015-09-01	0.038	202	326	35.87	1.98	99.28
2015-10-01	0.017	281	370	37.66	7	99.07
2015-11-01	-0.104	275	308	40	9.55	98.91
2015-12-01	-0.223	300	344	34.64	-2.45	98.85
2016-01-01	-0.124	1081	384	34.52	-20.28	98.94
2016-02-01	0.082	1017	506	35.58	-11.77	99.17
2016-03-01	-0.084	1085	450	36.11	6.07	99.43
2016-04-01	-0.063	975	436	34.92	5.48	99.56
2016-05-01	-0.032	1011	384	33.49	-11.32	99.68
2016-06-01	-0.192	868	427	33.55	-5.76	99.76
2016-07-01	-0.108	882	448	32.86	7.1	99.67
2016-08-01	-0.049	891	373	30.37	4.14	99.5
2016-09-01	-0.092	891	304	27.82	-7.24	99.55
2016-10-01	-0.081	1005	294	25.41	-7.69	99.73
2016-11-01	-0.011	897	252	26.61	11.69	100.02
2016-12-01	-0.007	834	170	30.57	16.58	100.36
2017-01-01	-0.088	952	268	32.78	10.01	100.66
2017-02-01	-0.142	825	240	32.24	3.41	100.83
2017-03-01	-0.061	952	275	33.15	-4.83	100.78
2017-04-01	-0.047	798	331	34.8	-6.6	100.61
2017-05-01	-0.027	824	334	37.39	0.77	100.61
2017-06-01	-0.116	813	155	38.22	2.14	100.8
2017-07-01	-0.095	777	150	36.36	4.54	100.98
2017-08-01	-0.143	795	211	37.43	-3.67	101.25
2017-09-01	-0.021	636	198	36.77	7.59	101.43
2017-10-01	-0.1	605	160	37.41	8.07	101.4
2017-11-01	-0.133	523	145	33.87	8.69	101.36
2017-12-01	-0.017	447	104	31.03	19.1	101.42
2018-02-01	-0.065	35	126	28.78	16.75	101.5

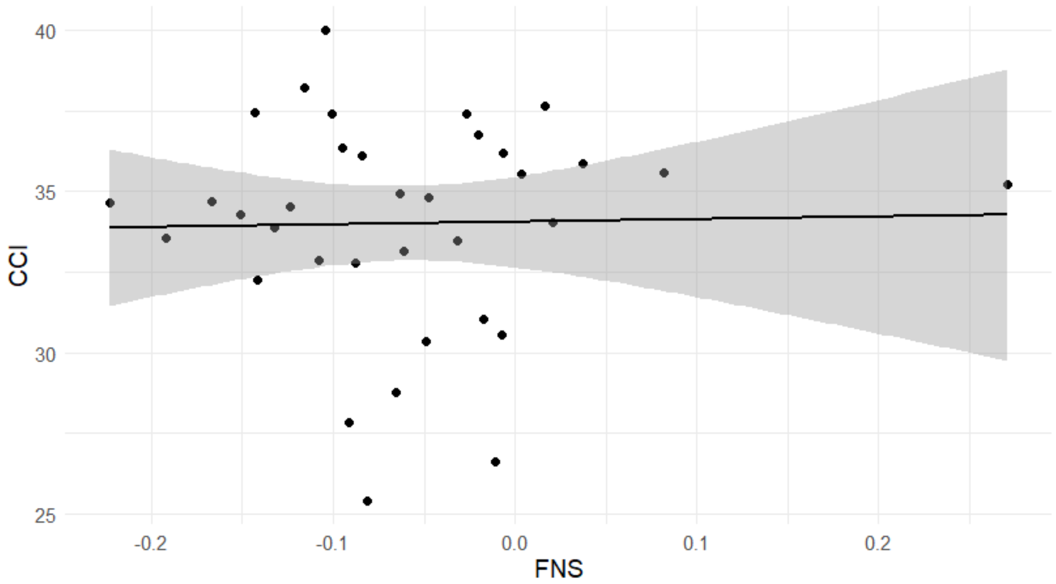
Source: Compiled by the author

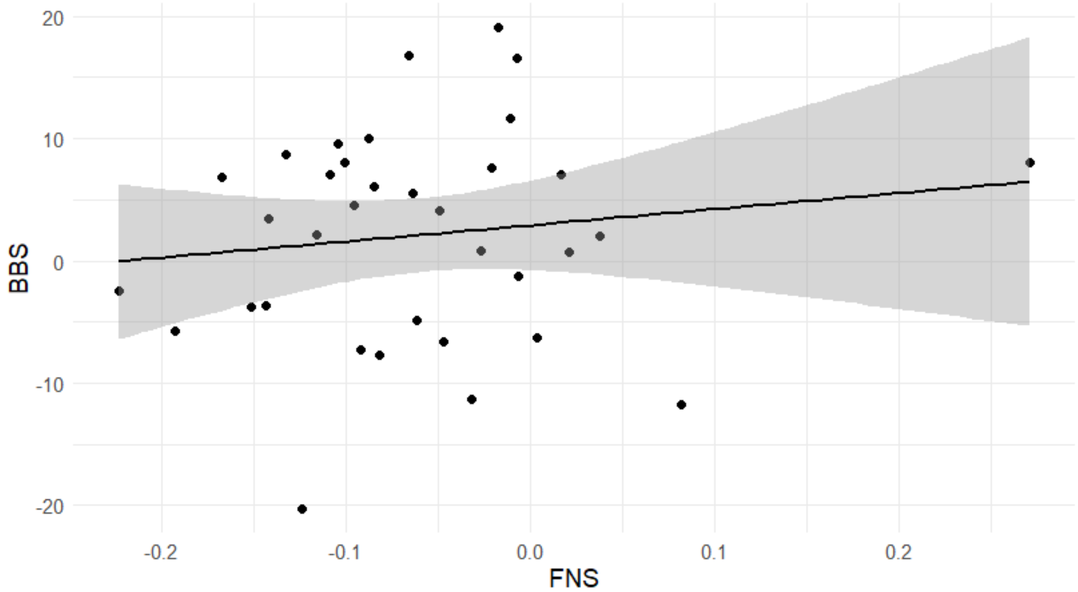
APPENDIX B

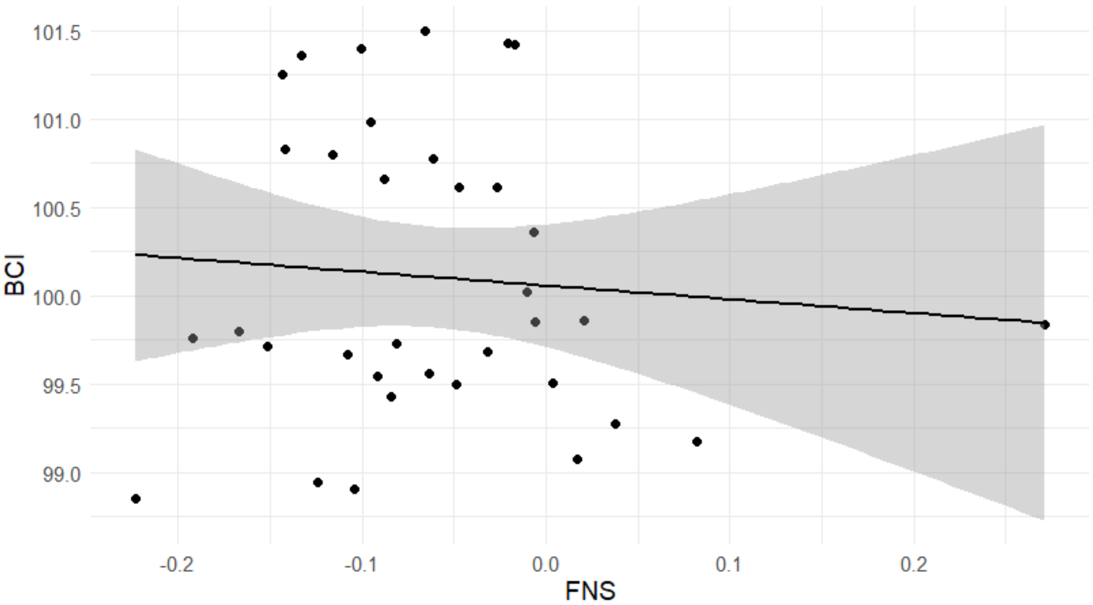
Correlation graphs

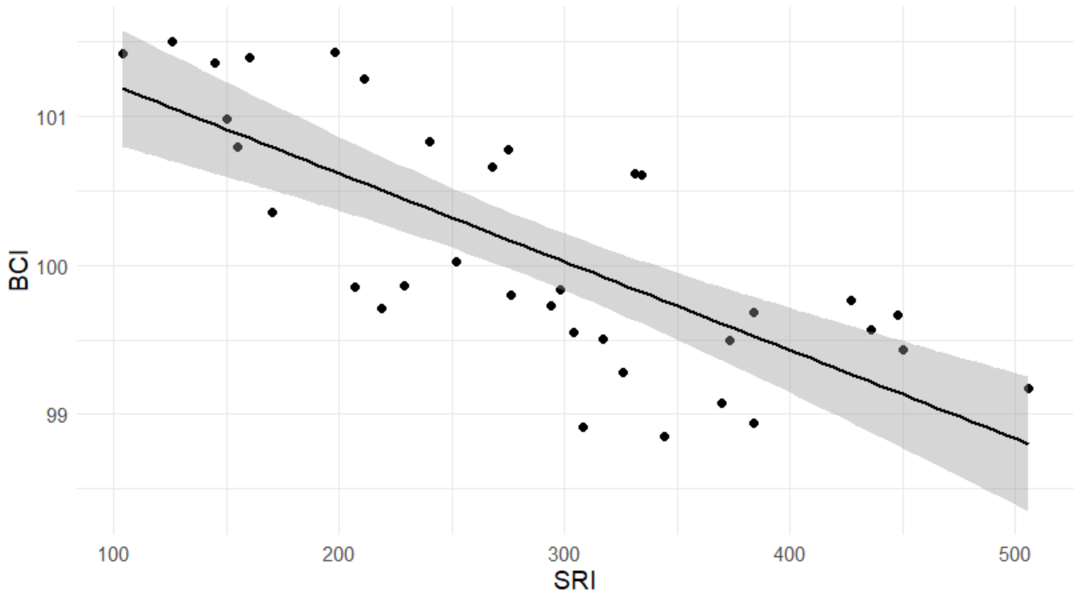
Source: Compiled using RStudio

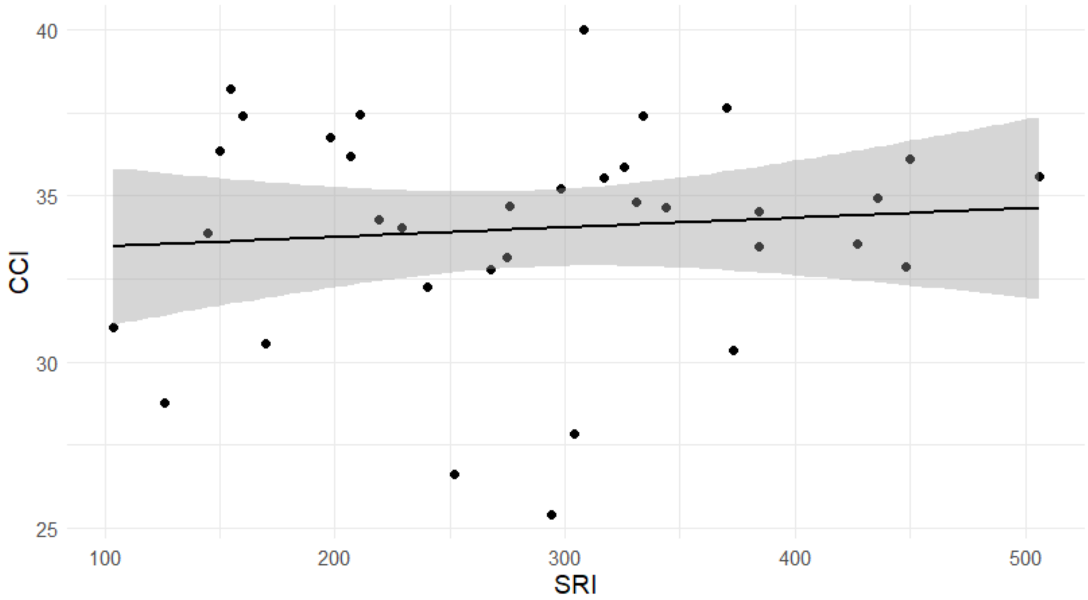


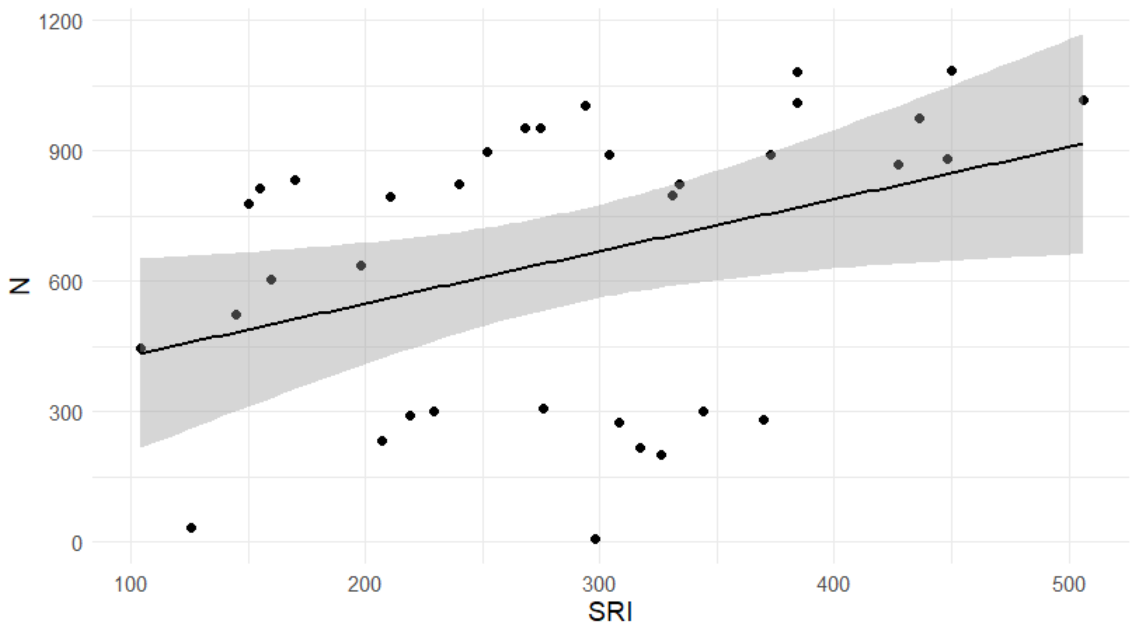

CCI
40
35
30
25
-0.2
-0.1
0.0
0.1
0.2
FNS

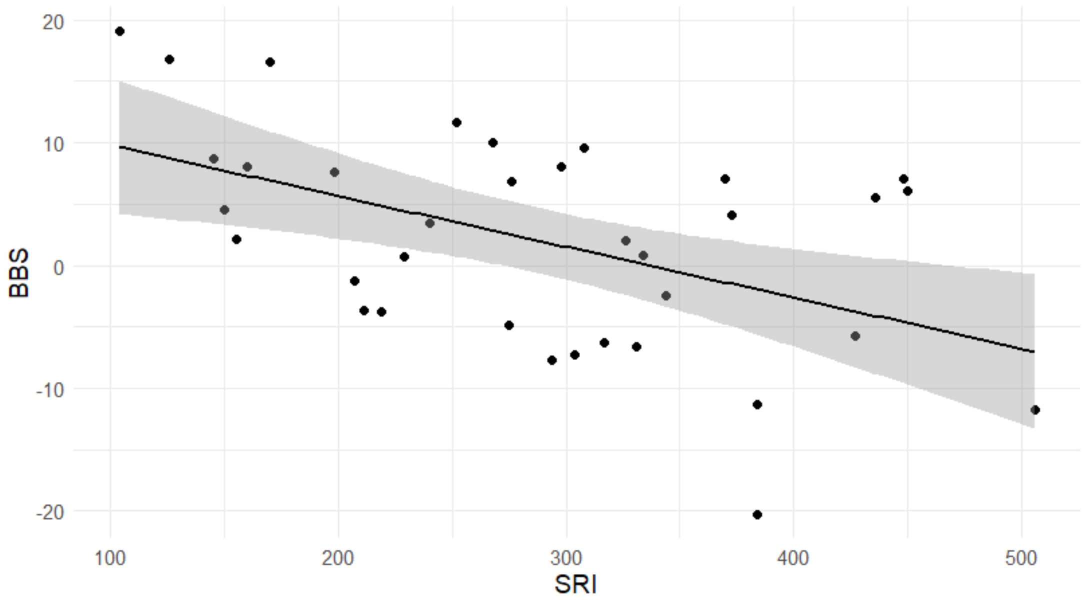

BBS
20
10
0
-10
-20
-0.2
-0.1
0.0
0.1
0.2
FNS

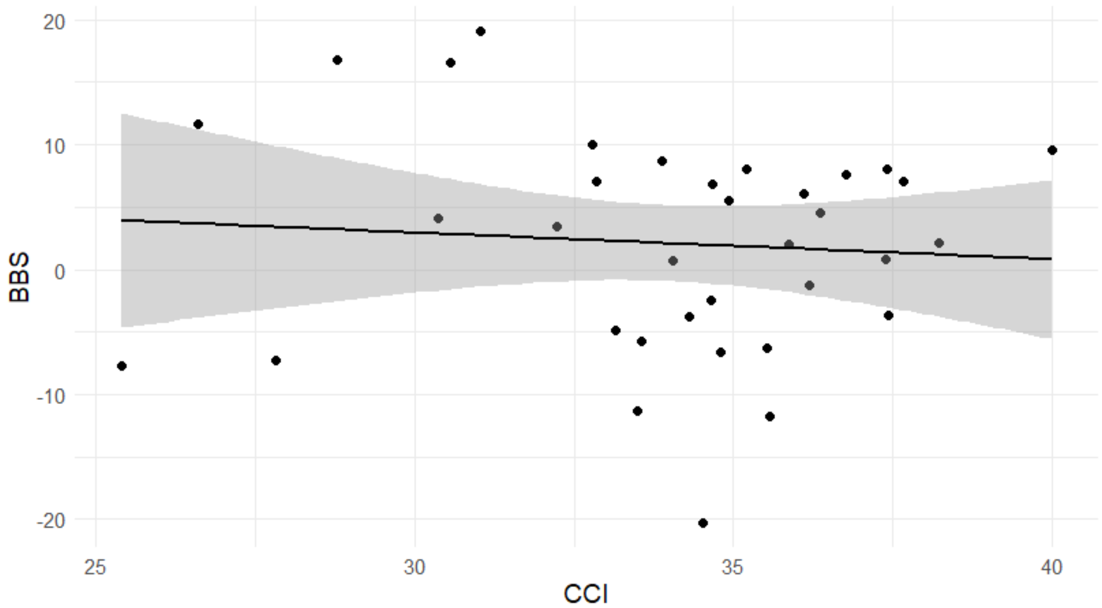

BCI
101.5
101.0
100.5
100.0
99.5
99.0
-0.2
-0.1
0.0
0.1
0.2
FNS

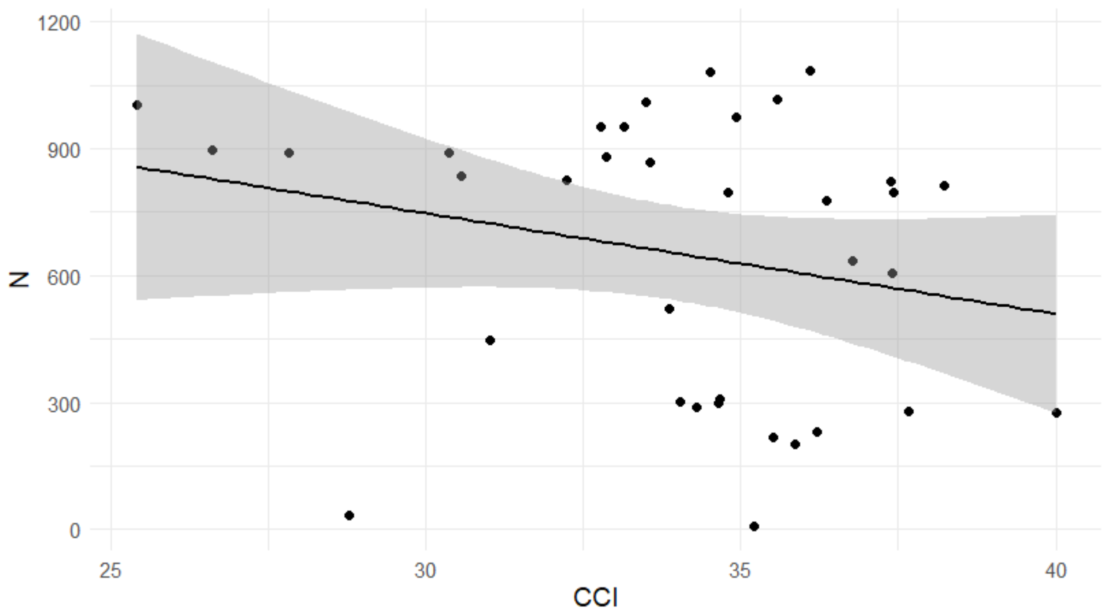

BCI
101
100
99
100
200
300
400
500
SRI

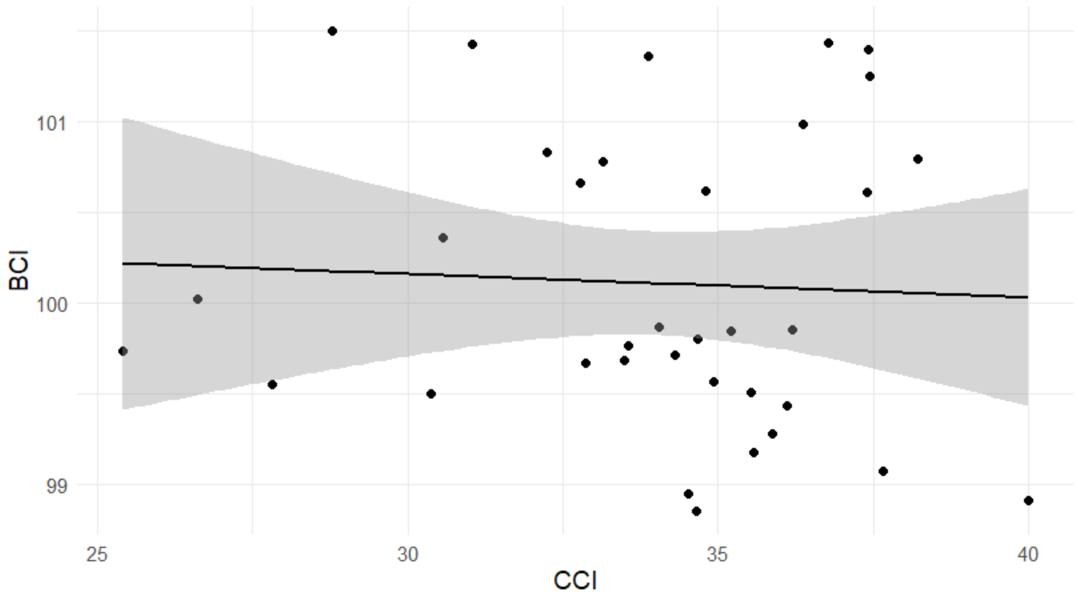

CCI
40
35
30
25
100
200
300
400
500
SRI

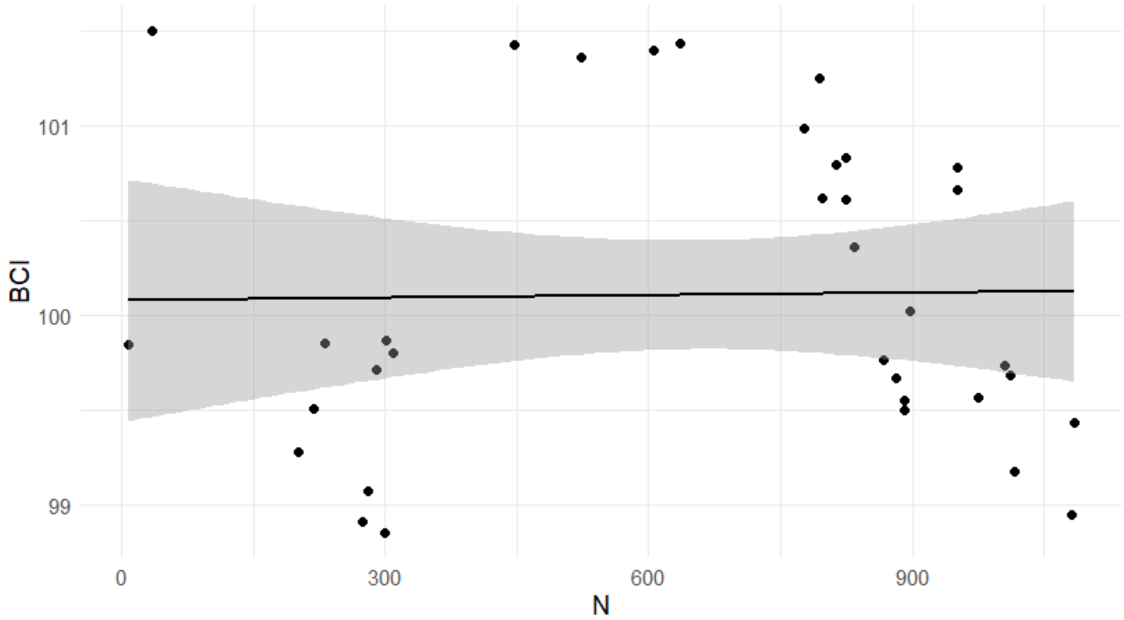

N
1200
900
600
300
0
100
200
300
400
500
SRI

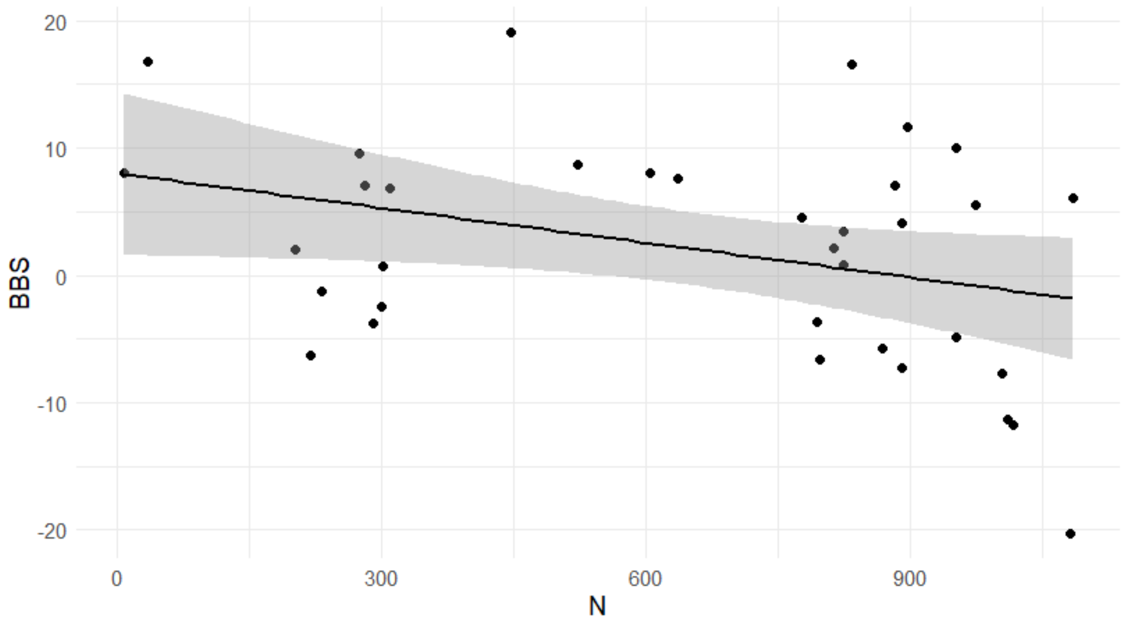

BBS
SRI
20
10
0
-10
-20
100
200
300
400
500

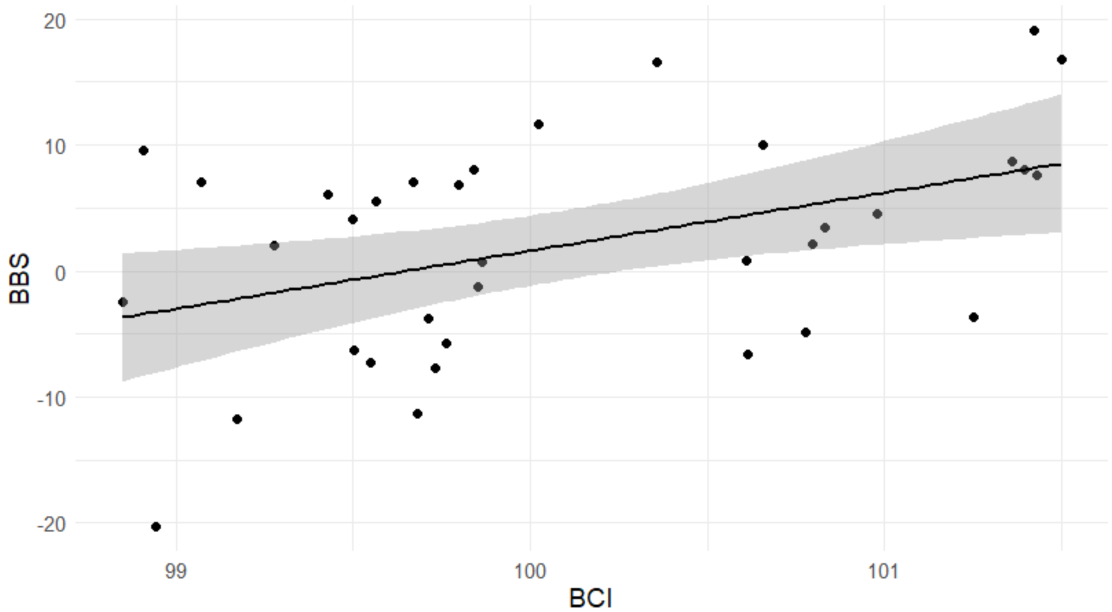

BBS
CCI
20
10
0
-10
-20
25
30
35
40


N
CCI
1200
900
600
300
0
25
30
35
40


101
100
99
BCI
25
30
35
40
CCI


101
100
99
BCI
0
300
600
900
N


20
10
0
-10
-20
BBS
0
300
600
900
N


20
10
0
-10
-20
BBS
99
100
101
BCI

APPENDIX C

Multivariate regression model

MANOVA
W = Wilks' lambda L = Lawley-Hotelling trace
P = Pillai's trace R = Roy's largest root

		Statistic	Df	F(df1,	df2) =	F	Prob>F
Model	W	0.4738	2	8.0	58.0	3.28	0.0037**
	P	0.5494		8.0	60.0	2.84	0.0096**
	L	1.0613		8.0	56.0	3.71	0.0015**
	R	1.0129		4.0	30.0	7.60	0.0002***
Residual				32			
FNS	W	0.9236	1	1 4.0	29.0	0.60	0.6656
	P	0.0764		4.0	29.0	0.60	0.6656
	L	0.0828		4.0	29.0	0.60	0.6656
	R	0.0828		4.0	29.0	0.60	0.6656
N	W	0.4982	1	4.0	29.0	7.30	0.0003***
	P	0.5018		4.0	29.0	7.30	0.0003***
	L	1.0071		4.0	29.0	7.30	0.0003***
	R	1.0071		4.0	29.0	7.30	0.0003***
Residual				32			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05
Source: Compiled using STATA

Coefficients

		Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
SRI	FNS	216.2898	193.6338	1.12	0.272	-178.1294	610.709
	N	.1335259	.0523047	2.55	0.016	.0269848	.240067
	cons	212.2189	36.87041	5.76	0.000	137.1163	287.3214
CCI	FNS	-1.647847	6.605867	-0.25	0.805	-15.10356	11.80786
	N	-.0025175	.0017844	-1.41	0.168	-.0061521	.0011172
	cons	35.54692	1.257843	28.26	0.000	32.98477	38.10906
BCI	FNS	-.7897432	1.685495	-0.47	0.643	-4.222984	2.643497
	N	-.0000117	.0004553	-0.03	0.980	-.0009391	.0009157
	cons	100.0652	.3209402	311.79	0.000	99.41142	100.7189
BBS	FNS	4.686655	16.88908	0.28	0.783	-29.71528	39.08859
	N	-.0087374	.0045621	-1.92	0.064	-.0180301	.0005553
	cons	8.081847	3.215902	2.51	0.017	1.531269	14.63242

Source: Compiled using STATA

Resümee

Vääruudiste mõju süsteemsele riskile ja arvamuste indikaatoritele USA-s

Lana Botchorishvili

Selles uuringus analüüsime vääruudiste ja vääruudiste arvamuste mõju süsteemsel riskil ja arvamuse indikaatoritel USA-s. Oleme valinud andmestiku mis koosneb 23467. vääruudisega artiklist 2015. aasta 31. märtsist kuni 2018. aasta 19. veebruarini. Kasutame sõnastiku-põhilist analüüsi paketti, et hinnata arvamuse indikaatoreid vääruudise tekstis. Avastasime, et vääruudiste negatiivsus ja positiivsus ei mõjuta ega seostu ei süsteemse riski ega turumeeleoluga USA-s. Peale vääruudistega artiklite kokku liitmist kuu kaupa ja nende süsteemse riski indikaatori arvutamist leiame, et nende vahel on statistiliselt oluline suhe. Avaldatud vääruudiste artiklite hulga ja investorite meeleolu vahel leidsime negatiivse suhte. Sobitades regressioonimudelit suhte ulatuse määramiseks leidsime, et vääruudistega artiklite maht mõjutab süsteemset riski tugevalt. Järeldame, et vääruudistega artiklite maht mõjutab majanusraskuste kogust turul.